

# **The Impact of Switching Stores on State Dependence in Brand Choice**

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# **The Impact of Switching Stores on State Dependence in Brand Choice**

## **Abstract**

This paper examines the relationship between store switching and state dependence in consumer brand choice. The classic structural state dependence literature models inertia in brand choice by assuming that consumers experience an extra boost in utility from consuming the products they last purchased. We demonstrate that the level of inertia depends on the context in which the purchase was made, which suggests that a richer decision process is driving the state dependence. Specifically, we find that consumers exhibit more state dependence if they shop at the same store that they previously patronized as compared to if they switch to a different store. This result replicates across 18 consumer packaged goods (CPG) supermarket categories. We find that the median consumer's increased state dependence from shopping at the same store vs. a different store translates into an additional 33¢ premium (or 12% of the average price) per purchase. When consumers switch back to a store they previously visited, both the brand purchased on the last shopping occasion (at the different store) and the brand purchased the last time the consumer was at the same store influence the consumer's decisions, but the consumer is more influenced by the last purchase they made at the particular store they are currently patronizing. We also find consumer responsiveness to other elements of the marketing mix depend on which store the consumer shops at: If the consumer changes stores, they exhibit greater sensitivity to price and feature advertising. However, store switching has no consistent influence on the impact of in-store displays on consumer choice. We conclude by discussing possible theories behind the results.

## 1. Introduction

This paper studies the role that store switching has on the extent to which consumers demonstrate state dependence. We show that consumers exhibit greater state dependence when they shop at the same store as the one at which they made their previous purchase in the category as compared to the level of state dependence they exhibit when they shop at different stores. This impact of the shopping context on state dependence contrasts with the current utility view of state dependence.

Marketers have put state dependence into their choice models since at least Guadagni and Little (1983), which found that putting a consumer's past purchases into a choice model significantly increased the fit of the model. One key question that has been raised is whether the inclusion of a last purchase, or loyalty, variable truly captures state dependence, or whether the variable captures unobserved preference heterogeneity. For example, Keane (1997) observes that the measured state dependence shrinks when better models of heterogeneity are used, although he does not find that state dependence disappears completely. However, several other papers have shown that the presence of state dependence is not merely an artifact of an incomplete specification of homogeneity.<sup>2</sup> Further, Seetharaman et. al. (1999) show that state dependence is a household characteristic that persists across categories, although the intensity of state dependence varies across categories. The presence of state dependence has been shown to have strong effects on fundamental elements of the marketing mix. For example, building on the theoretical work of Klemperer (1995), Dubè, Hitsch and Rossi (2009) show that state dependence can lead to higher or lower equilibrium prices, and that at the estimated levels of state dependence, current prices in margarine and orange juice are lower than they would be in the absence of state dependence. Dubè et. al. (2008) also note that in the case of category pricing, state dependence incentivizes managers to decrease prices on high-quality products and increase prices on low-quality products.

In the structural state dependence literature, state dependence is conceived as a boost in utility that consumers gain from consuming the products that the consumers last purchased. This increase in utility can be viewed as either a literal increase in the utility from being in a state where consistency in the brand of a product that is being consumed leads to higher utility, or as a type of psychological switching cost, where consumers dislike an incongruity in the consumed brands in adjacent consumption experiences. In this conceptualization of state dependence, its effect should not depend on which store the

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<sup>2</sup> Gupta, Chintagunta and Wittink (1997) separate heterogeneity and state dependence using the ordering of purchases. Erdem and Sun (2001) present a series of tests to prove state dependence. Dubè, Hitsch and Rossi (2010) use both a flexible demand specification as well as model-free evidence to demonstrate that state dependence truly exists. Shin, Misra and Horsky (2012) combine survey data and purchase data to separate heterogeneous preference from inter-temporal effects. Despite the advances made in accurately estimating state dependence, challenges remain. For example, Paulson (2012) shows that there can be an initial conditions issue that arises when choice models are estimated using short panels. We estimate our choice models using only consumers who made at numerous purchases in a category partially to mitigate these concerns.

consumers shopped at, but rather it reflects a true preference shock based on past consumption. In contrast, our results demonstrate that the impact of state dependence depends on the context in which the purchase was made – in particular, whether the store in which the purchase is made matches the store in which the consumers made their last purchase. If the consumer changes stores, they exhibit less state dependence, greater price sensitivity, and an increased responsiveness to feature advertising, although there is no systematic effect of changing stores on display advertising.

There are several reasons why changing stores might affect the size of state dependence. First, consumers switching stores might be less familiar with the new store, leading the consumer to engage in a search process they would avoid at a store they were more-familiar with. Such a search would change the decision process from a decision rule that requires low amount of processing to one that is more informed, resulting in lower state dependence and greater price sensitivity. A similar effect is that consumers may regularly use constructed decisions (Amir and Levav 2008 Drolet, Simonson and Tversky 2000) or habits (Wood and Neal 2009) to make decisions. These decisions have been shown to be highly dependent on the context in which the choices are made, where the decision or habit rules are only engaged when the consumer finds him or herself in a similar situation as the past experiences over which the decision rule was formed (e.g., Neal, Wood, Labrecque and Lally. 2011, Neal, Wood, Wu and Kurlander 2011). Some of the choice cues that may differ across stores include assortment sizes (Iyengar and Lepper 2000), signage guiding consumers to deals (Goodman, et. al. 2012), the proximity of rival products (which can change the comparison set), which products are at eye level (Amir and Levav 2008), or the ambiance or even background effects can send different signals about what the right product is (North et. al. 1997, Simonson 1999).

Choice modelers have understood that psychological factors can affect choices. For example, Bucklin and Lattin (1991) estimate a two-state choice model, where consumers can either be planners (who have state dependence but do not respond to store cues) or opportunists (who respond to store cues but not to state dependence). They find that consumers who exhibit high loyalty to a store tend to be planners when they go to that store. Seetharaman (2004) estimates a model with both structural state dependence as well as habit. He finds that structural state dependence is the most-important type of state dependence, but that habit also has a measurable impact on choice and the estimated parameters. Johnson et. al. (2006) use click-stream data about how consumers searched for their products and combine this with choice data to estimate a model of choice process and choice outcomes.<sup>3</sup> Hansen and Singh (2009) estimate a model where consumers can focus on different product attributes depending on the format of the store (which can be a traditional supermarket, a high-end store, or an EDLP stores). They show that the extent to which specific products are substitutes changes across the different formats. There is also an

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<sup>3</sup> Kim et. al. (2010) go a step further and use only search process data to estimate demand.

empirical literature that studies how the context of the anticipated consumption (rather than the context of the store at which the consumer is shopping) affects the brand that is chosen (e.g., Yang, Allenby and Fennell 2002), or even the type of product that is chosen (Huang, Khwaja and Sudhir 2012).

Our paper proceeds as follows. In Section 2, we discuss the data that we use in our estimation. In Section 3 we provide some descriptive statistical analysis suggesting that consumers shop differently if they shop at the same store versus different store from their previous purchase occasion. In Section 4, we estimate a series of choice models which form the basis of our analysis. Section 5 synthesizes and concludes.

## **2. Data**

This paper's analysis is based on the IRI Academic Dataset (Bronnenberg, Kruger and Mela 2008). In particular, we use the individual panel dataset of grocery-stores purchases in 2003-2006. Our analysis is based on consumer decisions in 18 categories: beer, coffee, deodorant, diapers, facial tissue, frozen dinner, frozen pizza, laundry detergent, margarine, mayonnaise, paper towels, peanut butter, shampoo, soup, spaghetti sauce, toilet paper, tooth paste and yogurt. Note that these categories are quite diverse, both in their level of differentiation, as well as in the extent to which the categories are thought of as being traffic drivers. Overall, the individual level panel includes over 8138 households across two cities. However, only a subset of these households make purchases in any given category. For the choice model analysis, we only include households that have made at least 9 purchases in whichever category is being studied, partially to reduce initialization concerns (Paulson 2012). The number of households utilized in the choice-model estimation varies by category, but across categories we use an average of 3200 households (range = 273 for diapers, 776 – 6026 for other categories), with an average of 30 – 40 purchases (range 17.6 – 112) by each household.

We estimate which brand a consumer chooses, conditional on the consumer making a purchase in the category. Brands are created from the product-line (L5) key in the IRI database, by taking out the spaces from a name, comparing each of the names, and substituting the shorter of the two names if there is overlap between a shorter and a longer name. We assume that consumers choose among a set of “top” brands, or else choose an outside option if they choose a product in the category that does not belong to a top brand. The “top” brands are selected by ranking the brands by the number of purchases made by the panelists, and including brands starting from the most-popular brand and going in decreasing order of popularity, until the set of included top brands includes 70% of the market. However, in no case are more than 6 top brands considered.

The marketing mix elements we include in the estimation are price, feature advertising, displays (we treat major and minor displays equally) and a price promotion dummy which IRI defines as being

equal to 1 when there is a temporary price reduction of 5% or more. However, different SKUs belonging to a brand may have different values for each of these variables. Thus, we construct the brand's price to be the total revenues spent on the brand at a particular store in a given week, divided by the volume-equivalent units of the brand that we sold in that store in that week. A brand is considered to have feature advertising if any SKU at that store during the particular week had feature advertising. Display and price promotion are defined analogously.

### 3. Descriptive Analysis

In this section, we present descriptive evidence that consumers make choices differently after changing stores. We first present the evidence, and then demonstrate that the descriptive analysis may understate the extent to which store-switching affects state dependence in brand choice.

In Table 1, we present the average rates of repeat purchase at the SKU, product line and brand levels under two contexts.<sup>4</sup> These numbers are the averages of the repurchase rates that are calculated separately for each of the 18 categories. In the first context, consumers make a purchase in the same category in the same store where they last made a purchase in the category. In the second context, consumers make the purchase at a different store than where they last purchased in the category. The results in Table 1 are averages of these same percentages in the 18 categories listed in Section 2.<sup>5</sup> In column 1, we see that across all trips that consumers choose the same product as they last bought 23.5% of the time, while the consumers choose to buy the same product as they last bought 13.8% of the time.<sup>6</sup> Looking at brand purchases, consumers buy the same brand as they last bought 42.5% of the trips where they shop at the same store as they last shopped at when making a purchase in the category, but only 34.0% of the time when they change stores.

One obvious concern with the calculations in the first column of Table 1 is that one reason why consumers may not repeat their purchase is that the product they last purchased may not be available on their next shopping trip. This concern is especially heightened for different SKUs across different stores, but can be an issue even within a given store. For example, in the deodorant category, consumers have relatively large inter-purchase times, and the exact product they bought may no longer be available. This changing of exact items is one reason why the choice-model analysis is conducted at the brand level. To

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<sup>4</sup> The descriptive results in Tables 1 and 2 are based on all households in the panel that make any number of purchases in multiple weeks, not just the households that buy 9 or more units.

<sup>5</sup> While the IRI data provide information about all supermarket trips taken by each household, we consider only the trips where consumers buy a product in the focal category. Our goal is not to explain why consumers do not buy laundry detergent in every shopping trip, for example, but under which conditions the consumer is more or less likely to buy the same brand of laundry detergent at the time they next buy laundry detergent.

<sup>6</sup> If a consumer buys multiple brands on a shopping trip, then they are said to buy the same brand on the next shopping occasion if they buy any of the brands they bought in a previous trip. All trips are indexed by the week of the trip, so trips to multiple stores in the same week are counted as occurring at the same time.

get around the availability issue, in column 2 we present the amount of repeat purchasing that occurs when both the previously-purchased and the currently-purchased products are both available in the respective stores in both the last and current shopping period. We can see that the general pattern of column 1 carries over to column 2, although the differences between repeat purchase when the customers go to the same vs. different stores shrinks substantially for the “both products available” case. Nevertheless, the average probability of buying the same product (brand) as the consumer bought in the previous shopping trip is 14% (20%) higher when they shop at the same store versus when the consumer switches stores.<sup>7</sup>

While it may at first naively seem clear that the second column of Table 1 correctly measures the difference in the propensity to make repeat purchases if the consumer shops at the same versus different store, the results in column 2 are actually biased *against* finding that the brand repurchase rates are higher at the same store than they are when consumers switch stores. To understand the source of this bias, consider two cases as shown in Figure 1. In the first case, the customer shops at the same store in weeks 1 and 2. Because the consumer is shopping at the same store, most of the products on the shelf are the same across the two weeks. Suppose that in week 1 the store offers products A, B, C, D and E, while in week 2 the store offers A, B, C, D and F. Suppose that consumers just choose products randomly; in such a case, the probability that a consumer makes a repeat purchase conditional on both products being available is 1/4. One can see this by noting that if the customer buys product A in week 1, then they will make a repeat purchase if they buy A again, but be included in the dataset if they buy A, B, C or D. However, if the consumer buys product F in week 2, then that purchase occasion will not be in the dataset since product F was not available in the previous week.

Suppose, on the other hand, that the customer shopped at a different store in weeks 1 and 2, and that the consumer again chooses products randomly. Typically there is greater variation in the cross-sectional product offerings across stores than in the intertemporal product offerings within a store over time. Suppose that the store the consumer shopped at in week 1 and week 2 have two out of 5 products in common, as seen on the right-hand side of Figure 1. Then the probability that a consumer repeats their purchase conditional on both products being available is 1/2. Thus, we can see that limiting our analysis to cases where both brands that are available biases the results against finding that repurchase rates are higher when the customer shops at the same store compared to a different store; In this example, consumers who had no state dependence would exhibit twice as high rates of repurchasing a product if

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<sup>7</sup> The qualitative pattern in Table 1 holds across all 18 categories, except for the SKU repeat purchase probabilities when both products are available for Mayonnaise and Shampoo, where the probability of repeat purchase at the same store is 3% or 1% *lower* than the probability of repeat purchases at different stores. See the discussion in the next paragraph about why requiring that both products be available creates a bias towards finding higher repurchase rates when consumers switch stores, and this bias is especially likely to be a large concern for the SKU-level analysis.

they switched stores compared to the repurchase rate if they stayed in the same brand. This bias is especially problematic at the SKU level where two retailers might sell two products that are extremely similar, but differ slightly. This bias, and the bias in the opposite direction that occurs from not considering availability at all, is a key reason why we estimate a choice model for our main analysis, since a choice model correctly accounts for the availability of the different products.<sup>8</sup>

Another concern one might have about the previous example is that one of the top brands in most categories is the “Private Label” brand. IRI treats all private label brands as being bundled into one brand across stores. While there is some evidence that consumers treat private labels as being somewhat consistent across stores (Szymanowski and Gijsbrechts 2012), it is possible that consumers do not equate the private labels at different stores as being equivalent. In column 3, we rerun the analysis, keeping only cases where both products are available in both the previous and past weeks, and remove any cases where either the previous or current purchase is a private label. The qualitative results are unchanged.

In column 4, we consider whether income effects may be driving our results. One may believe that low-income individuals are less likely to be loyal, and more likely to search across their options at all stores; the demographic estimates from the choice model confirm this intuition. In such a case, if poorer individuals engaged in a different choice pattern we might expect to see a different pattern of relative repurchase rates emerge. Instead, we find that the patterns are largely stable across the full set of individuals and low-income individuals.

Finally, we consider whether other marketing mix factors might be affected by which store the customers patronize. Table 2 reports the average fraction of the time that consumers buy products on display, feature or price promotion if they are at their favorite store as compared to if they are at another store.<sup>9</sup> We see that consumers are more-likely to buy products on feature, display or promotion at non-favorite stores, relative to favorite store. While the average effect is for consumers to be more-likely to buy in any of these three conditions at a non-favorite store, the difference in probabilities for display between the favorite store and other stores is not statistically significant,<sup>10</sup> and there are some categories where customers are more-likely to buy the products on display at their favorite store. This ambiguity for display translates into observed results in the choice model.

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<sup>8</sup> An argument in the other direction is that prices may be more stable within a given week, so the higher repurchase rates within a store could be due to more-consistent relative prices than consumers face across stores. Here, again, a choice model accounts for these factors.

<sup>9</sup> Favorite store is defined by the store that is visited for the greatest number of shopping trips for all trips across the four years in the dataset, not only trips where the category is purchased.

<sup>10</sup> Statistically significant in the sense of sampling the mean probabilities across categories, and calculating the standard error for this mean across 18 observations (with each category as one observation).

#### 4. Choice Model

While the previous section provides descriptive evidence that consumers may behave differently after switching stores, we also note that the descriptive analysis suffers from biases that make it difficult to measure the extent to which supermarket context effects the impact of state dependence. Therefore, we estimate a brand-choice model.<sup>11</sup>

I estimate separate brand-choice models for each of the 18 categories. The brand choice model is based on the consumer maximizing utility, where the utility that consumer  $i$  gets from consuming brand  $b$  on shopping trip  $t$  is:

$$U_{i,b,t} = \beta_{i,b} + X_{b,t}\gamma_i + I(Store_t = Store_{t-1})X_{b,t}\delta_i + \varepsilon_{i,b,t}. \quad (1)$$

In this specification,  $\beta_{i,b}$  represents a brand-specific utility term for consumer  $i$  when they purchase brand  $b$ , and  $X$  includes price, a feature advertising dummy, a display dummy, a price promotion dummy, and a last-purchased term, which we also call a loyalty or state dependence term. Note that all of the coefficients are consumer-specific. We assume that the coefficients are normally distributed in the population: Formally, let  $\theta_i = (\beta_i, \gamma_i, \delta_i)$ . Then  $\theta_i \sim N(\bar{\theta}, V_\theta)$ , where  $\bar{\theta} = \Delta'Z$ ,  $Z$  includes a constant and demographic terms for income (an indicator variable indicating whether income is below \$35,000) and age (an indicator variable indicating that age is at or above 65), and  $V_\theta$  represents the variance-covariance matrix for the parameters. We allow all of the off-diagonal terms to deviate from zero, allowing for any plausible covariance matrix. The  $\delta_i$  term represents the incremental impact that the marketing mix has on a consumer's utility if that consumer is shopping at the same store as they shopped at in their previous trip. Thus, the impact of the marketing mix on utility if the consumer shops at a different store than they shopped at in the previous week is given by  $\gamma_i$ , while the impact of the marketing mix on utility if the consumer shops at the same store as they shopped at previously is  $(\gamma_i + \delta_i)$ .<sup>12</sup>

As noted previously, I only include up to 6 large inside brands per category. The consumer may also choose to consume a minor brand (which includes any brand that is not specifically estimated). In such a case, they are treated as if they consumed the outside good, and obtain a utility of:

$$U_{i,0,t} = I(Last_t = Other)\gamma_{i,Loy} + I(Store_t = Store_{t-1}) \cdot I(Last_t = Other)\delta_{i,Loy} + \varepsilon_{i,0,t}. \quad (2)$$

In words, the outside option delivers a utility of zero, and is not attributed to having price, feature or display characteristics, since it is a combination of so many different products. However, consumers who

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<sup>11</sup> We estimate the brand that the consumer purchases conditional on the consumer making a purchase in the category during a given shopping trip. We do not model the choice of whether to consume in the category or which store to patronize.

<sup>12</sup> In the case where the consumer visits multiple stores in a given week, and makes a purchase in the category at both stores, the interaction term  $I(Store_t - Store_{t-1})$  is equal to 1 in the next week that they make a purchase if any of the stores from the previous week.

last purchased a minor brand may have state dependence to the outside option, and the extent to which this state dependence impacts utility can depend on whether the consumer switched stores or not.

The random utility term,  $\varepsilon_{i,b,t}$  is an independent i.i.d. extreme value I error, so the probability that the consumer purchases brand  $j$  on a given trip  $t$  is given by

$$\Pr(b = j | X, Store_t, Store_{t-1}) = \frac{\exp(U_{i,j,t})}{\exp(U_{i,0,t}) + \sum_{b=1}^J \exp(U_{i,b,t})}. \quad (3)$$

where  $J$  is equal to the number of top brands. We estimate the model using a Bayesian MCMC approach and specify a hierarchical prior consistent with the hierarchical multinomial logit model as expounded in chapter 5 of Rossi, Allenby and McCulloch (2005). The estimation converges quickly, but to ensure a robust sampling of the prior, we make 37,500 draws from the posterior distribution. To save hard-disk space and memory while estimating models from so many categories, we keep every 25<sup>th</sup> draw, and discard the initial 12,500 draws as an initial burn-in. (The estimates are extremely similar even if no burn-in is used, reflecting how quickly the estimation moves to parameter region corresponding to a high likelihood.)

### **The Impact of Store Switching on State Dependence**

The details about the categories, number of households and trips used in the estimation are provided in Section 2. The mean of the household-specific state dependence terms in both  $\gamma$  (the state dependence if a consumer switched stores) and  $\delta$  (the incremental increase in the impact of state dependence on utility if the consumer shops at the same store as in the previous shopping occasion for the category) are positive for all 18 categories, and the means in each case are statistically different than zero (in the sense that the 0.95 posterior credibility region of the means of these coefficients never includes zero). This means that there is state dependence in the brand choices of consumers in all categories, but also the state dependence is stronger if the consumer shops at the same store rather than switching stores, for all categories.

How much larger is the state dependence when customers shop at the same store relative to when they switch stores? We can calculate the relative impact of state dependence in these two contexts by taking the ratio of the total state dependence when the consumer goes to the same store compared to the state dependence when they go to a different store:  $\frac{\gamma_{Last} + \delta_{Last}}{\gamma_{Last}}$ . The average of this ratio is 2.20 across

categories, and Table 3 shows the mean ratio for this effect for each of the included categories. The range of the mean ratio varies from 1.42 for beer to 3.84 for paper towels. The fact that the ratios are so far from 1 – the minimum ratio still finds that the size of the state dependence when a consumer shops at the same

store is 42% higher than the size of the state dependence when the consumer shops at a different store – suggests that the context of the consumers’ decision has a large impact on the extent to which consumers exhibit state dependence in their brand preferences. Table 3 also provides an intriguing look at which products are more impacted by the context of the shopping trip. It seems plausible that the product categories that have the largest variation between the different brands’ products are beer, shampoo, toothpaste, yogurt, soup, frozen dinners and frozen pizzas. The non-frozen items with the most product variation are products that have a lower ratio (i.e., products where the context of the purchase matters least). This appears to be consistent with the hypothesis of the constructed decisions literature which suggests that context should matter most for those categories where consumers have the hardest time justifying their decisions based on observable attributes. An alternative theory for why switching stores could matter is that consumers may engage in more of a search mode when they are in a different supermarket than their last trip. In this case, the cues they look for in a relatively differentiated category may be the product attributes they like, while in a relatively undifferentiated category the consumers may look for marketing attributes to help them make their decisions. The frozen aisle may cut short this search due to being a relatively unpleasant place to spend time.

Another way to measure the impact of the store context on state dependence is to measure the extent to which consumer’s brand repurchase rates will differ if they shop at the same vs. different stores. Table 4 shows the different repurchase rates that would be observed if consumers shopped at the same vs. different stores in the coffee category. To compute these transition probabilities, we treated each draw of each household’s estimated preference parameters as a separate individual. We matched each consumer to the initial brand purchased condition by assigning that consumer to the brand they last purchased in our dataset. Thus, the consumers who are initially assigned to Folgers are not a random set of customers, but rather customers who actually last consumed Folgers, and therefore have a disproportionate preference for Folgers. Comparing the repurchase rates across each of the top 4 coffee brands, we find that the repurchase probability is 6-10% higher if the consumer shops at the same store on their next coffee trip as compared to if they shop at a different store. Thus, the different state dependent coefficients are not only statistically significant, they also have an economically-meaningful size. Note that the cross-purchase probabilities, which show that consumers from each of the 4 brands tend to switch to one of the larger brands if they switch at all, comes from the estimated covariance of preferences, and is not a forced pattern from our model.

Finally, Dubè, Hitsch and Rossi (2010) quantify the dollar value price premium that would offset the state dependence coefficient as being the negative ratio of the state dependence coefficient divided by the price coefficient. We calculate a similar number, which is the dollar value of the marginal increase in the state dependence from purchasing at the same store. This is calculated as the coefficient on the

incremental increase of state dependence from shopping at the same store, divided by the price coefficient:  $-\frac{\delta_{Last}}{\gamma_{Price}}$ . We calculate the distribution of this ratio for each category, and in Table 5, we summarize the average of this distribution of this effect across categories. We find that the median consumer's increased state dependence from shopping at the same store vs. a different store translates into an addition 33¢ premium per purchase. Note that the prices in each category are computed for 1 unit of a typical purchase. Thus, in most cases, the prices reflect the actual average amount paid per purchase. However, there are some categories where there is a large amount of variation in the package sizes the different households purchase. For example, prices in the beer category are priced in terms of dollars per case, but the price premium we would calculate would be 1/4 the size we currently calculate if we instead based our estimation in on the volume-equivalent price of a 6-pack of beer. To get around this issue, we divide the price premium by the average price for an item in the category. We find that the median consumer trades off about an extra 12% price premium for the increased state dependence from shopping in the same store.<sup>13</sup>

Finally, we note that in contrast with much of the switching cost literature, we do estimate a few demographic effects that stand out as often being statistically significant. We find that low-income individuals are generally more price sensitive (6 out of 18 categories), less sensitive to their past purchases (6 out of 18 categories, with 1 out of 18 with the reversed sign), and more context dependent in the sense that the differences in their levels of state dependence if they shop at the same store vs. a different store is larger than the same difference for the population at large (5 out of 18 categories, with 1 out of 18 again with the reversed sign). Thus, low-income individuals appear to engage in a fuller search approach if they experience a change in their shopping environment, but freeing themselves of the cues that might lead to an subconscious decision rules has a larger payoff for these individuals. We also find that seniors are more price sensitive (5 out of 18 categories) and more responsive to feature and display activity (4 out of 18 categories each, with one reversal of sign for feature). However, seniors do not appear to have much of a context effect.

### **Robustness Across Specifications**

One concern that a reader could raise about the previous analysis is whether the estimated context effects on the state dependence estimates actually capture some unobserved consumer heterogeneity, in the flavor

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<sup>13</sup> We can compare our numbers to the premium from state dependence as calculated by Dubè et. al. (2010) in the margarine data (based on a different dataset). They find that the median consumer trades off 14¢, or 12% of the price for state dependence in the margarine category. We find that the incremental tradeoff for the increased state dependence in that category is 19¢ or 15%, and the ratio of the same-store to different-store state dependence is about 2:1. Thus, the estimates are broadly consistent, although we estimate a more diffuse distribution of a price premium.

of the overall academic literature on the estimation of state dependence (e.g, Keane 1997, Erdem and Sun 2001, Dubè, Hitsch and Rossi 2010, Paulson 2012). Note that the estimation of the incremental effect of shopping at the same store on the estimate of state dependence is identified off of the different rates of loyalty within a consumer’s purchase history depending on whether they switched stores or did not switch stores in a particular trip. However, one may worry that the decision to switch stores is endogenous to a broader evolving set of preferences.

While we do not address the endogenous store choice question directly, we conduct two robustness checks to give some confidence in the robustness of the result. First, one may worry that customers that switch stores often are less loyal overall than customers who switch stores rarely. Given research (Ainslie and Rossi 1998, Seetharaman, Ainslie and Chintagunta 1999) that shows that consumer responsiveness to the marketing mix is largely a consumer trait across categories, it might be reasonable to surmise that consumers who are more “loyal” to a store exhibit greater loyalty to products. One may then worry that the greater loyalty that is estimated for trips to the same store really reflects the greater loyalty of exhibited by consumers who shop at the same store more often. This would be a functional form concern, since in theory the overall propensity for a person to be loyal to a brand should be captured by the state dependence parameter in  $\gamma$ .

In order to address this concern, we re-estimate the choice models for each category using only consumers whose Herfindahl index (HHI) on their portfolio of store visits is below  $\frac{1}{2}$ .<sup>14</sup> Note that because we are concerned that the loyalty to a store may reflect a personality trait, we calculate the store HHI based on the distribution of shopping trips to stores across all trips (and not only trips where consumers buy a product in the category). The upper limit of  $\frac{1}{2}$  on the HHI ensures that we are estimating the model on consumers who are not too loyal to a particular store. We can measure the effect that limiting the estimation to these consumers have on our estimates by taking the mean of the ratio of

$$\frac{\text{Same-store state dependence} / \text{Different-store state dependence for Low Herfindahl}}{\text{Same-store state dependence} / \text{Different-store state dependence for all customers}}. \quad (4)$$

The closer this ratio is to 1, the less of a selection effect occurs. Across all categories, the average value of this ratio is 1.07, with a standard deviation of 0.12 and a range of 0.85-1.33, across categories. Thus, it

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<sup>14</sup> The Herfindahl index is used extensively in anti-trust cases, and is calculated as  $\sum_{k=\text{stores}} s_k^2$ , where  $s_k$  is the fraction of trips the consumer takes to store  $k$ .

appears that the extent to which a consumer shops at many stores does not explain very much of the incremental difference in state dependence based on the context of the shopping trip.<sup>15</sup>

Another concern one may have is that the decision to switch stores may reflect an evolution in the consumer's preferences. This would mean that the propensity to change brands would be correlated with the propensity to change stores. In order to assess whether this is a concern, we estimate a model that allows for consumer preferences to depend not just on whether the consumer shopped at the same store, but to also consider their behavior in the trip just before they are about to change stores. Thus, the utility is now modeled as being

$$U_{i,b,t} = \beta_{i,b} + X_{b,t}\gamma_i + I(\text{Store}_t = \text{Store}_{t-1})X_{b,t}\delta_i + I(\text{Store}_t = \text{Store}_{t-1}) \cdot I(\text{Store}_t \neq \text{Store}_{t+1})X_{b,t}\omega_i + \varepsilon_{i,b,t}. \quad (5)$$

If we are capturing an effect that is truly from store switching, we expect the coefficient on  $\omega_{Last}$  to be zero, while if the store switching was capturing evolving tastes, we would expect  $\omega_{Last} = -\gamma_{Last}$ . Overall, we find that the mean for  $\omega_{Last}$  is not significantly different from 0 in 11 cases, and in the 7 cases where  $\omega_{Last}$  is significantly different from 0, the sign on  $\omega_{Last}$  is positive, not negative. Further,  $\omega_{Last}$  is less than  $\gamma_{Last}$  in all but one category. Calculating the overall ratio of the coefficient of state dependence just before a consumer switches to another store to the coefficient of state dependence for other periods where the consumer shops at the same store, we get a ratio of 1.14, which is close to one. Thus, we conclude that such heterogeneity is not a major concern.

### **Which history matters when a consumer returns to a store**

In the previous discussion, we demonstrate that the impact of state dependence is lower when consumers shop at a different store than they previously visited. In this section, we consider which past purchases affect choices when a consumer switches back to a store they had previously shopped at. In particular, we measure whether the last purchase made at the previous shopping occasion matters more, or whether the last purchase at the particular store the consumer is returning to matters more. If search and habit behaviors are driving our results, then the last purchase made at the particular store should matter. In contrast, if traditional structural models of state dependence are right – and the measured state dependence measures a switching cost or a shift in preference from past purchases – then the last purchase should matter the most.

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<sup>15</sup> The impact that loyalty to a supermarket, as measured in the supermarket HHI, has on the other marketing mix elements is small for price, display and feature, which have corresponding ratios of 1.05, 1.00 and 1.11, respectively. The ratio of price promotion is far from 1, but also has such a huge variance as to make the test devoid of meaning.

To measure the extent to which the most-recent purchase versus the purchase from the most-recent trip to the particular store matters more, we run a modified brand choice model with the following functional form:

$$U_{i,b,t} = \beta_{i,b} + X_{b,t}\gamma_i + I(b_t = b_{t-1})\lambda_i + I(b_t = b_{Last\ trip\ to\ same\ store})\psi_i + \varepsilon_{i,b,t}. \quad (6)$$

In this equation,  $X$  includes price, feature, display and price promotion variables.  $\lambda_i$  represents the increase in utility that the consumer obtains if they consume the last brand they purchased, and  $\psi_i$  represents the increase in utility the consumer obtains if they consume the brand that they purchased on their most-recent trip to that particular store. In order to avoid double-counting state dependence effects when  $b_t = b_{Last\ trip\ to\ same\ store}$  due to our assumed linear function form, we estimate this model only from observations where the consumer had been to the store at some previous trip, where that store was not visited during the week of the most-recent previous purchase in the category, and where  $b_t \neq b_{Last\ trip\ to\ same\ store}$ , although the results appear to be robust to relaxing these assumptions.

The results demonstrate that the last brand purchased at the particular store has a larger influence on the purchase decision than the last brand purchased overall. The average value of  $\bar{\psi}/\bar{\lambda}$  across the 18 categories is 1.28, with a standard deviation of 0.29. The ratio is less than 1 for only two categories: diapers, where there are only 223 observations from 30 households (so the model is quite poorly estimated and neither  $\bar{\psi}$  nor  $\bar{\lambda}$  are meaningfully distinct from 0), and Yogurt, where the ratio is 0.93. Also,  $\bar{\psi}$  and  $\bar{\lambda}$  are significantly positive in the sense that 0 is never within the Bayesian confidence interval for all of the categories except  $\bar{\psi}$  and  $\bar{\lambda}$  for diapers and  $\bar{\psi}$  for toothpaste. These results show that both the last purchase overall and the last purchase at the particular store matter, but that the last purchase at a particular store has a greater impact. This suggests that the structural state dependence literature's literal interpretation of consumers switching between states is incomplete. Rather, the last item purchased in the particular store also matters, suggesting that there may be a habit or search process playing a part in consumers' decision processes as well.

### Context and the Marketing Mix

This paper emphasizes the role that the context of which store a consumer shops at has on consumers' choices. However, the context of a shopping trip also impacts consumers' sensitivity to different elements of the marketing mix. The estimated model in equation (1) also provides estimates for the different impact that price, feature advertising, and displays have when the consumer is shopping at the same store vs. switching stores.

The mean of the main price coefficient,  $\bar{\gamma}_{price}$ , is negative and significantly different from zero for all 18 categories. Further, when consumers shop at the same store as their most-recent trip, they are less price sensitive. The average incremental effect of price when the consumer makes a purchase from the same store they shopped at previously,  $\bar{\delta}_{price}$ , is positive for all 18 categories, although the Bayesian confidence interval excludes zero for only 11 out of 18 of the categories. The average ratio of the total price sensitivity when a consumer shops at the same store as their previous trip as compared to when they shop at a different store is  $\frac{(\bar{\gamma}_{Price} + \bar{\delta}_{Price})}{\bar{\gamma}_{Price}} = 0.925$ . Thus, on average, consumers tolerate about 8% higher prices when they shop at the store they last shopped at compared to when they switch stores.

Another form of price sensitivity is the boost in utility the customer gets when an item is on price promotion. For 14 of the 18 categories, we observe that price promotions increase consumer utility, but that the increase is greater when the consumer switches their stores compared to when they shop at the same store. Overall, the ratio of  $\frac{(\bar{\gamma}_{Promo} + \bar{\delta}_{Promo})}{\bar{\gamma}_{Promo}} = 0.47$ , reflecting a greater sensitivity to promotions when the consumer changes stores. However, the means of the price promotion coefficients,  $\bar{\gamma}_{Promo}$  and  $\bar{\delta}_{Promo}$  are only *both* significantly different from zero in 5 categories, and in four categories at least one of the coefficients has an incorrect sign. Although it is worth noting that the results are broadly consistent with the findings from a price coefficient, I plan to drop price promotion from future revisions of this paper.

The average sensitivity of feature advertising is larger when a consumer changes stores. The average direction of this effect holds for 13 out of 18 categories, and is statistically significant for 7. Different underlying processes lead to different patterns in the coefficients for feature advertising. If the difference in behavior when shopping at the same store vs. a different store was based on a change from an automatic to a deliberative decision process, one would expect feature advertising to have the same impact at the same vs. different stores, because feature advertising must be utilized before the shopping trip. On the other hand, consumers might expect greater returns from reading the feature for the store they last visited, and thus one might expect feature advertising to have a greater effect when the consumer patronizes the same store they previously visited. Conversely, one might expect feature advertising to have a greater impact at rival stores if it is one of the key tools to cause customers to switch stores. Finally, the impact of feature advertising at the same store may be diminished because while the consumer intends to buy the product advertised in the feature, they may forget to switch from their usual

brand to the featured brand because habit overrules their intentions (ala Ji and Wood 2007). While we remain agnostic about the underlying process, one of the latter two effects appears to dominate.

Finally, there is no clear difference in the impact that displays have on consumer utility depending on where they shop. In particular, the coefficients on the marginal context effects for display advertising,  $\bar{\delta}_{Display}$ , are insignificant for 12 out of 18 categories, significantly positive for 3 categories, and significantly negative for 3 categories.

Overall, these findings on the relationship between store consistency and price, feature and display are somewhat congruent with the findings of Seetharaman, Ainslie and Chintagunta (1999), which finds that state dependence is correlated with lower price and feature sensitivity. However, in Seetharaman et. al., these sensitivities are estimated to be household characteristics, while our focus is on the way that these sensitivities are driven by the context of a particular shopping trip.

## **5. Synthesis and Conclusion**

This paper demonstrates that consumer state dependence varies based on the context of the store they are visiting. In particular, consumers are more state dependent when they are shopping at the same store they patronized when they made their last category purchase, as opposed to a different store. We further demonstrate that price sensitivity and responsiveness to feature advertising are diminished when consumers shop at the same store as compared to when they switch stores. These results contrast with the structural state dependence literature, which interprets the state dependence as being a psychological switching cost that should be independent of the shopping context.

There are several plausible reasons that could explain our results. First, consumers that switch stores may also switch from making quick automatic decisions to engaging in a fuller search at a store with familiar product offerings. However, the fact that displays, which should facilitate search, have an equal impact on consumers regardless of whether the consumer switched stores suggests that search is perhaps not the best explanation. This is bolstered by the observation that there is very little correlation between the number of products in a category to that category's ratio of state dependence coefficient at the same store vs. a different store.

Another plausible explanation for the effect is that consumers engage in habitual decision making, and that these habits are store specific. In this case, the feature advertising might be less effective because consumers shopping at their previous store may intend to buy the featured item, but instead forget to do it and make their habitual choice instead. Also, it is plausible that displays disrupt habit

formation in either context, and therefore have comparable effects at either the same or a switched store.<sup>16</sup> That said, there are other plausible mechanisms for the results, including switching both stores and brands simultaneously as a form of joint variety seeking, or consideration set formation differing across stores. Testing between these explanations would be interesting, but goes beyond the scope of this project, which is simply to measure the extent to which state dependence varies across the two contexts.

There are several managerial implications to our findings. First, we know that the level of state dependence has significant impacts on pricing (Dubè et. al. 2008, Dubè et. al. 2009). Also, some supermarkets are likely to have more switchers than others. For example, supermarkets located in densely populated areas or in urban centers probably experience greater consumer switching, which leads to greater price sensitivity in addition to the heightened competitive pricing pressure these outlets already face from higher competition. Similarly, there has been movement towards increased multi-store shopping. Our results suggest that one likely effect is that consumers will act less habitually and therefore be more price sensitive.

Our results also suggest that store manager may want to consider creating a super-loyalty program. Right now, several chains have loyalty programs, but the rewards tend to be linear in spending, so there is not much incentive for a consumer to concentrate all of their purchases to a given store. In contrast, store managers may want to create a loyalty program that has convex benefits, like we observe in airlines rewards programs, in order to create lock in. The retailer would then have fewer consumers switching between stores, which would allow them to capture some of the consumer's increased willingness-to-pay, as discussed during the analysis of Table 5.

Finally, Dick and Basu (1994) suggest that a retailer may want to push their consumers to purchase especially profitable items. The fact that consumers do not transfer their state dependence across stores suggests that manufacturers hoping to promote items through push marketing will need work with all major retailers to push their products, since hooking consumers at one store does not immediately translate state dependence at another store. The fact that consumers return to the product they last consumed at a particular store does suggest that push marketing can lead to long-term customer relationships at a particular store, however.

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<sup>16</sup> An additional model unreported in this paper suggests that a display may disrupt the consumer's habitual response, even if the display is for the product they would have bought on habit.

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Figure 1: Assortment Match Possibilities in Two Scenarios

	Same Store	Different Store
Week 1	A B C D E	A B C D E
Week 2	A B C D F	A B F G H

Table 1

		All Trips	Both Prods Avail	No Private Labels	Income < \$35,00
SKU	% Same Store Repeat	31.8%	36.9%	37.7%	0.0%
	% Different Store Repeat	18.7%	32.7%	33.3%	0.0%
	Extent Same Store is higher than Different Store:		14%	14%	0%
Product Line	% Same Store Repeat	50.2%	51.5%	53.0%	0.0%
	% Different Store Repeat	38.1%	42.5%	45.2%	0.0%
	Extent Same Store is higher than Different Store:		22%	18%	0%
Brand	% Same Store Repeat	57.5%	58.2%	60.6%	0.0%
	% Different Store Repeat	46.0%	49.0%	52.7%	0.0%
	Extent Same Store is higher than Different Store:		20%	16%	0%

Table 2

	Favorite Store	Other Store
Display	0.17	0.21
Feature	0.25	0.33
Price Promo	0.28	0.37

Table 3 Ratio of brand-level state dependence at same store vs. different store

1.42	Beer
1.65	Shampoo
1.66	Toothpaste
1.82	Laundry Detergent
1.87	Mayonnaise
1.90	Yogurt
2.01	Margarine
2.05	Soup
2.07	Peanut Butter
2.13	Diapers
2.23	Deodorant
2.25	Coffee
2.40	Facial Tissue
2.57	Frozen Dinner
2.66	Toilet Paper
2.84	Frozen Pizza
2.96	Spaghetti Sauce
3.84	Paper Towels

Table 4 Brand Repurchase rates as function of whether consumer shops at same vs. different store.

Transition probabilities when consumers shop at the same store					
People buying this brand:					
		Folgers	Maxwell House	White Cloud	Eight O'Clock
Next buy this brand	Folgers	60%	17%	15%	9%
	Max. House	9%	48%	13%	5%
	White Cloud	4%	6%	41%	4%
	Eight O'Clock	2%	2%	3%	57%

  

Transition probabilities when consumers shop at a different store					
People buying this brand:					
		Folgers	Maxwell House	White Cloud	Eight O'Clock
Next buy this brand	Folgers	54%	19%	18%	11%
	Max. House	11%	42%	15%	7%
	White Cloud	5%	7%	31%	5%
	Eight O'Clock	3%	2%	4%	49%

Table 5: Value of Component of State Dependence Effect Attributable to Context

Percentile	Cents	% Increase
10%	-206	-61%
25%	-47	-12%
50%	33	12%
75%	128	41%
90%	291	89%